

# Technological diversification within UK's small serial innovators

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**Abstract** This paper investigates the determinants of technological diversification among UK's small serial innovators (SSIs). Using a longitudinal study of 339 UK-based small businesses accounting for almost 7000 patents between 1990 and 2006, this study constitutes the first empirical examination of technological diversification among SMEs in the literature. Results demonstrate that technological diversification is not solely a large firm activity, challenging the dominant view that innovative SMEs are extremely focused and specialised players with little technological diversification. Our findings suggest a nonlinear (i.e. inverse-U-shaped) relationship between the level of technological opportunities in the environment and the SSIs' degree of technological diversification. This points to a trade-off between processes of exploration and exploitation across increasingly volatile technology regimes. The paper also demonstrates that small firms with impactful

innovations focus their innovative activity around similar technological capabilities while firms that have introduced platform technologies in the past are more likely to engage in technological diversification.

**Keywords** Diversification · Small serial innovators · SME · Technological opportunity · Relatedness · Fractional response model

**JEL Classifications** L6 · L20 · O31 · O32 · L26

## 1 Introduction

It is widely recognised that the growing complexity of technology development in both cognitive and relational dimensions has resulted in an increasing technological diversification, defined by research activities over more than one technology (Breschi et al. 2003), within highly innovative companies (Patel and Pavitt 1997; Fai and von Tunzelmann 2001). In particular, technological diversification has been found to constitute a pervasive element in firms characterised by persistent innovation over time, with the large majority of persistent innovators being highly diversified in their innovative activities (Breschi et al. 2003), allowing them to survive and grow avoiding technological lock-ins (David 1985; Suzuki and Kodama 2004). Accordingly, previous research has shown that technological diversification is an important

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competitive advantage among companies operating in dynamic innovation environments (Gambardella and Torrisi 1998), with increasing empirical evidence pointing to a positive relationship between diversification, innovation performance and innovative competencies (Garcia-Vega 2006; Quintana-Garcia and Benavides-Velasco 2008; Modrego et al. 2015).

However, previous literature has mainly focused on large firms to explore underlying patterns of knowledge relatedness, technological scale and scope, and the management of technological diversification (Granstrand et al. 1997; Granstrand 1998; Fai 2003; Lin and Chang 2015), following the perspective that ‘the problem has not been deciding where to go, but how fast and effectively to get there’ (Patel and Pavitt 1997, p. 154). Conversely, very little attention has been paid to the relationship between technological diversification and small firms mostly due to the expected differences in the level of resources across large and small firms and the high costs of integration, coordination and the scale of R&D capabilities that technological diversification requires (Vossen 1998; Wang and von Tunzelmann 2000; Ortega-Argilés et al. 2009; Lin and Chang 2015).

Yet, the increasing division of labour in innovation defined by developing markets for technology and innovation networks have brought to the fore the importance and the contribution of small companies characterised by an unusually high level of innovative activity over time (Arora et al. 2001; Hicks and Hegde 2005; Libaers and Meyer 2011). Thus, considering the activity of R&D intensive small firms with persistent patterns of innovation, coined as small ‘serial innovators’ (SSIs) in the literature (Hicks and Hegde 2005; Corradini et al. 2015), two questions naturally arise: (1) how can SSIs resolve the fundamental tension between patterns of specialisation and diversification within their technological trajectories? and (2) what are the determinants behind the technological diversification processes? On one side, technological diversification plays a central role in increasing firms’ absorptive capacity, enabling them to explore and exploit new opportunities, allowing for economies of scope in technology development (Granstrand et al. 1997; Granstrand 1998). On the other side, the resource-constrained essence of many small firms dictates a specialised nature of innovative activities defined by the cumulative quality of technological change around firms’ core technologies (Antonelli and Scellato 2015;

Nelson and Winter 1982; Dosi 1982). Since the management of cumulated technological capabilities is crucial for the survival and success of these innovative SMEs (Hicks and Hegde 2005; Corradini et al. 2015; Máñez et al. 2015), examining the patterns and determinants of technological diversification are highly relevant research objectives that are currently under-researched in the small business literature. These objectives are in line with the emerging stylised facts about the unique nature of innovation activities undertaken by SMEs (Audretsch 1995; Ortega-Argilés et al. 2009; Rammer et al. 2009; Taymaz and Üçdogruk 2009; Antonelli and Scellato 2015) and highlight the need for in-depth enquiries into different dimensions of SMEs’ innovative behaviour including persistence and diversification (Coad and Guenther 2013; Colombo et al. 2014; Deschryvere 2014).

The paper offers three main contributions to the SME literature. First, using a data set of 339 UK-based small companies accounting for almost 7000 patents over the period between 1990 and 2006, this study constitutes the first empirical examination of technological diversification among SMEs in the literature. Our findings suggest that technological diversification activities are not limited to large firms as commonly presumed by the literature challenging the dominant view that innovative SMEs are extremely focused and specialised players with little technological diversification. Secondly, we explore the role of the technological environment in shaping the patterns of technological diversification across SSIs. Our findings suggest a nonlinear, inverse-U-shaped, relationship between the level of technological opportunities in the environment and the SSIs’ degree of technological diversification, pointing to a trade-off between processes of exploration and exploitation across technology regimes with increasingly higher rates of patenting activity. Finally, the paper focuses on the role of firm-specific technology characteristics on the diversification patterns of persistently innovating SMEs. In particular, we demonstrate that firms with impactful innovations tend to focus their innovative activity around similar technological capabilities, while firms that have introduced platform technologies (Kim and Kogut 1996) in the past are more likely to engage in technological diversification.

The structure of the paper is the following. The second section provides an overview of the specific literature and defines the research hypotheses of the

paper. The third and fourth sections discuss, respectively, the data set and the model used for the empirical analysis. Stylised facts about technological diversification among SSIs and the discussion of the findings are offered in the fifth section, followed by concluding remarks in the last section.

## 2 Literature review and hypotheses

Technological diversification literature has grown in line with the trend of increasing complexity and interconnectedness within technological innovation environments defined by the presence of multi-technology processes and products (Granstrand et al. 1997; Fai 2003). Technological diversification presents opportunities for cross-fertilisation between different technology fields and fosters economies of scale and scope, as well as speed and space, in innovation (Granstrand 1998).

Technological diversification within firms' innovation activity is usually associated with the need to monitor and increase firm capabilities in relevant technological fields that may be complementary to the firm's core business (Gambardella and Torrisi 1998). Such ability to recognise and absorb opportunities in new fields is cited as a fundamental capability for the long-term survival of technology-based firms (Fai and von Tunzelmann 2001; Breschi et al. 2003; Suzuki and Kodama 2004). Diversification increases the breadth of technology fields available for the firm's search scope and enables acquisition of the essential absorptive capacity to engage with technological opportunities in these new fields (Cohen and Levinthal 1990; Patel and Pavitt 1997; Quintana-Garcia and Benavides-Velasco 2008; Lin and Chang 2015). Innovative firms need to diversify their technological search efforts in order to reach above and beyond their immediate technological trajectory built through a combination of highly cumulative technology-specific learning patterns and firm routines (Nelson and Winter 1982; Dosi 1982; Malerba and Orsenigo 1993; Dosi and Nelson 2013; Malerba et al. 2013). Diversification enhances firm's combinative capabilities defined by the recombination of accumulated knowledge into new ideas, and broadens its technological competencies exerting a stronger effect on exploratory rather than exploitative innovation capabilities (Garcia-Vega 2006; Quintana-Garcia and Benavides-Velasco 2008).

In the absence of diversification efforts, technological lock-in effects pose a significant threat to the long-term survival of the company (Arthur 1994), particularly in industries that experience major transformations led by radical technological change (Suzuki and Kodama 2004; Patel and Pavitt 1997; Granstrand et al. 1997). Technological diversification may also lead to risk reduction in research activity, as diversified technology portfolios can lower the volatility associated with research projects increasing the overall return from innovation (Garcia-Vega 2006).

In the above-mentioned literature, technological diversification is implicitly seen as being mostly relevant to large firms. Instead, small innovators are defined as specialised players with little or no technological diversification, usually trying to acquire the complementary competencies required for innovation through explorative technological alliances (Rothwell and Dodgson 1994; Arora et al. 2001; Narula 2004). As the resource limitations that severely affect most SMEs inherently limit their ability to strategically diversify, the benefits to diversifying technological investments for small firms are highly conditional on the characteristics of the knowledge regime (Kim and Wang 2014). The significant impact of the technological environment on firms' knowledge accumulation strategies has long been recognised (Cyert and March 1963; Dosi 1982). Firms build specific routines to address the challenges in the environment and modify these routines in response to the demands of the particular technological context they operate in (Leonard-Barton 1992; Newey and Zahra 2009). In this sense, technological diversification among SSIs may result as a consequence of the dynamics of the technology environment where they operate and the nature and characteristics of the core technology they develop.

### 2.1 The relationship between technological opportunity and technological diversification for small serial innovators (SSIs)

In the innovation and technological change literatures, one of the key elements that characterise the technological environment surrounding a firm is constituted by the level of 'technological opportunities', defined as the set of possibilities available for technological advance (Nelson and Winter 1982; Malerba and Orsenigo 1993). Often, such opportunities reside in

different industries (Klevorick et al. 1995; Mowery and Rosenberg 1998). Firms need an extensive knowledge base if they want to recognise new avenues of research and be actually capable of assimilating new external information. Thus, similarly to the arguments presented for large multinational companies in the previous section, growing technological opportunities defined in terms of increasing rate of innovation across firms in the sector may generate incentives for SSIs to explore new avenues of research and expand their technological competencies. Under such circumstances, SSIs may also implement technological diversification as an organisational adaptation strategy (Brown and Eisenhardt 1995) in order to manage the increasing levels of technological opportunities associated within growing technological trajectories (Tushman and Rosenkopf 1992; Almeida and Kogut 1997). Through technological diversification, SSIs may build a broader basis of absorptive capacity, minimising the probability of being locked into a specific technology or locked out of a promising technological field (Suzuki and Kodama 2004; Toh and Kim 2013).

Even though a positive relationship between the level of emerging technological opportunities at the sectoral level and the SSI level of technological diversification is expected, it should be noted that an inherent tension exists between technological diversification and firms' ability to maintain a coherent knowledge and competence base as technological investments get spread into multiple technology fields. Firms are bound by their specific technological capabilities. In particular, persistent innovators have been shown to benefit from increasing returns defined by previous research activities (Peters 2009; Raymond et al. 2010; García-Quevedo et al. 2014). Within these cumulative dynamics of competence accretion, diversification is inherently characterised by knowledge relatedness defined by proximity, commonality and complementarity in learning processes (Breschi et al. 2003). Indeed, various authors have underlined the importance of maintaining the coherence of the firm's knowledge base throughout technological diversification efforts in order to effectively benefit from the cross-fertilisation across different technological fields and to deliver successful outcomes (Nesta and Saviotti 2005; Miller 2006; Leten et al. 2007; Quintana-Garcia and Benavides-Velasco 2008; Chiu et al. 2010). Resembling the trade-off between exploration and

exploitation in learning (March 1991; Fleming 2001), this tension between the need to diversify technological efforts and to maintain a coherent knowledge base defined by related firm-specific technological capabilities is likely to be most evident for small innovators. Various forms of resource limitations (Ortega-Argilés et al. 2009), along with the restricted access to external finance (Brancati 2015), introduce significant challenges to the depth and breadth of innovation activities that small firms can undertake. On the one hand, relying on processes of search depth and, therefore, technological specialisation helps small innovators make the most out of their R&D investments through maintaining a strong focus in a narrowly defined technological area (Hicks and Hegde 2005; Corradini et al. 2015). Yet, on the other hand, technological diversification is essential to better cope with the rapidly changing technological environments characterised by high levels of technological opportunity and uncertainty.

We expect the trade-off between specialisation and technological diversification for SSIs to tip in favour of specialisation particularly under technological environments characterised by increasingly higher levels of technological opportunities defined by uncertainty in the direction of technological change (Tushman and Rosenkopf 1992). Given the increasingly risky and resource intensive nature of exploration activities and the complexity in managing processes of knowledge coordination in such technological environment, technology specialisation is a more likely outcome (Toh and Kim 2013). In other words, the higher the rate of patenting within the technology environment the more limited the time and the resources available to explore and experiment the possibilities arising from inter-sectoral technological recombination (Stuart and Podolny 1996; Fleming 2001). This reduces the opportunities for engaging in processes of exploration of new research avenues away from the current technological capabilities. Accordingly, SSIs may retreat to specialisation as the main engine for future innovations in order to benefit from exploitation of internal, distinctive competencies along one specific technological trajectory under fast changing and uncertain technological environments (Kogut and Zander 1992; Corradini et al. 2015). In line with these arguments, our first hypothesis is defined as follows:

**Hypothesis 1:** Technological opportunities present an inverted-U relationship with respect to technological diversification among small serial innovators.

## 2.2 The impact of prior innovation on the technological diversification of SSIs

The focus on the elements of knowledge relatedness and coherence in explaining the extent and nature of technological diversification emphasises the importance of path dependence as an integral element of firms' technological trajectory (David 1985; Breschi et al. 2003). As persistent innovators are inherently defined by cumulative dynamics in knowledge creation (Peters 2009; Raymond et al. 2010; Archibugi et al. 2013; García-Quevedo et al. 2014), history governs the opportunities of diversification for the firm (Kim and Kogut 1996). For SSIs, the role of firm-specific technology characteristics on diversification is likely to be particularly prominent as their innovative process heavily relies upon the reuse and recombination of previous technological competencies to improve the selection and the exploitation of useful components in future innovation (Fleming 2001; Katila and Ahuja 2002). In particular, two specific characteristics that define the technological innovations can be associated with the development of technological diversification of SSIs: the *impact* and *generality* of innovation (Hicks and Hegde 2005; Corradini et al. 2015).

Impactful innovations are characterised by high levels of technological novelty added to the flow of new knowledge by the firm (Hicks and Hegde 2005). Impactful, high-quality innovations require significant amounts of resources for their development, limiting the ability of the firm to channel these resources to explorative activities in other fields. Therefore, firms with impactful innovations are likely to have fewer spare resources that can be channelled into technological diversification, especially if they are small firms with already limited resources. More importantly, impactful innovations define promising directions of technological search; therefore, they provide incentives for the firm's future research to follow on the same technological trajectory (Katila and Ahuja 2002). In this sense, firms with impactful innovations are also more likely to follow patterns of specialisation as their innovation has a higher likelihood of becoming a 'winner' in the technology race compared to innovations with lower impact (Toh and Kim 2013).

Accordingly, we hypothesise the relationship between the impact of the firm's innovations and its technological diversification as follows:

**Hypothesis 2:** The development of previous impactful innovations is negatively related to the degree of technological diversification in small serial innovators.

Generality of innovation describes technology that is generic and can be used for the development of a wide variety of technologies and products. Such innovations represent 'enabling technologies' characterised by high levels of dynamism and pervasiveness which generate processes of 'innovational complementarity' (Bresnahan and Trajtenberg 1995). Innovations defined by higher levels of generality may act as a 'platform' or a bridge that enables the diversification of firms' technological trajectory into derivative technologies (Kim and Kogut 1996). Hence, they increase the level of potential for exploration and reconfiguration of existing knowledge into new fields of research through diversification, allowing for a more fruitful exploitation of firms' combinative capabilities (Kogut and Zander 1992). Similar insights can be found in innovation studies building on the 'real options' literature where technological diversification is adopted by pharmaceutical firms with patents that have a larger number of potential application areas (McGrath and Nerkar 2004). Accordingly, we posit the following hypothesis:

**Hypothesis 3:** Higher levels of generality in the innovation activity of SSIs exert a positive effect on the level of technological diversification.

## 3 Data description

The data set used in this paper is based on all patents published<sup>1</sup> in the period between 1990 and 2006 by all UK small serial innovators (SSIs). Following previous literature (Hicks and Hegde 2005; Corradini et al. 2015), these companies are defined as independent companies having fewer than 250 employees<sup>2</sup> with at

<sup>1</sup> Single inventors or University applications were excluded.

<sup>2</sup> This definition follows the European Commission Recommendation (96/280/EC) of 3 April 1996, where SMEs are defined by the upper threshold of 250 employees. While this definition also includes medium sized companies, we use the term of small serial innovators in the paper to provide



least 10 patented inventions<sup>3</sup> distributed in a period of 5 years, and with an overall ratio of patents to years of technological activity equal or greater than 1. Patent data were obtained from the PATSTAT database and include assignee name,<sup>4</sup> patent publication date, technological field assigned by patent examiners, as well as backward and forward citations for each application. It is for its richness of detail that we use patent data. This choice is in line with most studies on technological competencies and diversification (Patel and Pavitt 1997; Garcia-Vega 2006; Quintana-Garcia and Benavides-Velasco 2008). Data on the patent technological field, which follows the International Patent Classification (IPC), have been reclassified into 30 different macro classes,<sup>5</sup> designed following Schmoch (2008) and Breschi et al. (2003). Economic data such as ownership, SIC code and merger and acquisitions were obtained from the FAME database and Companies House website, which provides information for all registered UK companies, as well as secondary sources such as companies' website. After excluding a set of companies for which it was not possible to obtain clear data on size and ownership,<sup>6</sup> the final data set contains information on 339 small companies accounting for 6948 patents over the period of time considered.

## 4 Model specification

### 4.1 Dependent variable

To measure *technological diversification* (TECHDIV), we use an index already employed in several empirical studies to estimate the effect of diversification on

innovation activity (Garcia-Vega 2006; Leten et al. 2007). It is calculated as the inverse of the Herfindahl index, confronting patents for each IPC technological class against the total number of patents of a  $i$ th company for each year  $t$ . Adjusting the index using the bias correction (i.e.  $N_{it}/N_{it} - 1$ ) indicated by Hall (2005) to account for observations with few patents per year, the index is formally defined as follows:

$$\text{TECHDIV}_{it} = \frac{N_{it}}{N_{it} - 1} \left( 1 - \sum_{k=1}^K \left( \frac{N_{it,k}}{N_{it}} \right)^2 \right) \quad (1)$$

where  $N_{it}$  is the total number of patents for the  $i$ th company in year  $t$ , while  $k$  represents the IPC category where the firm patented and  $K$  is the total number of technological classes where the company was active.

To explicitly take into account the relatedness in firms' diversification, we also define *technological relatedness* (RELATEDNESS) as a measure of how similar new patents are with respect to the firm's core competencies developed through time. We proceed calculating a knowledge-relatedness matrix whose elements are given by an index measuring the similarity between two technological classes with respect to their relationship with all other IPC classes (for a detailed description, see Breschi et al. 2003). Thus, we define the index  $\text{RELATEDNESS}_{it}$  for the  $i$ th company in year  $t$  as the average value of the knowledge-relatedness between each patent in time  $t$  and firms' core technological class. Following Breschi et al. (2003), the core technological class is defined for each company as the class where each firm has the highest share of patents with respect to the total number of patents at the UK level in that class.

### 4.2 Independent variables

We test our first hypothesis about the relationship between *technological opportunities* and diversification using a variable (OPPOR) measuring the increase in the rate of innovative activity for the technological classes where firms operate (Malerba and Orsenigo 1993). OPPOR is calculated for each firm as the average value defined by the year-over-year percentage increase in the number of patents for each IPC class where the firm patented, following the approach of Patel and Pavitt (1998). To account for the suggested curvilinear relationship with firms' technological

Footnote 2 continued

consistency with previous studies in the innovation persistence literature.

<sup>3</sup> Patent families were used as a proxy for firms' inventions, with patent family being defined as "a set of patents taken in various countries to protect a single invention" (OECD 2001). See Martinez (2011) for a detailed discussion on the use of patent families as proxies for firms' inventive activity.

<sup>4</sup> Data were manually checked to identify misspelled names or different names referring to the same entity.

<sup>5</sup> See Table 1. Only 28 technology classes are represented in our data, as no company in this sample operate in Nuclear and Surface Technologies.

<sup>6</sup> This includes companies which changed ownership and, therefore, presented multiple links with various business groups in the period of time considered.

diversification, we also add a squared term for OPPOR, which is expected to present a negative sign.

To test the effect of internal technology dynamics, we introduce in the model two different variables representing the impact and the generality of the patents developed by SSIs. The *impact of innovation* (IMPIN) is a measure of patents' quality, reflecting technological novelty added to the flow of new knowledge generated in a specific year and sector. To take into account the substantial differences in forward citation rates<sup>7</sup> across different technologies and over time, we make use of the citation index proposed by Hicks and Hegde (2005), defined for each patent as the ratio of the forward citations over the forward citation count of all patents in the same year and technological class. IMPIN is, then, obtained as the average of this citation index across firms' patents for each year. More formally, we have:

$$\text{IMPIN}_{it} = \frac{1}{P_{it}} \sum_{p_{it}=1}^{P_{it}} \frac{N_{fp_{it},k}}{N_{ft,k}} \quad (2)$$

where  $N_{fp_{it},k}$  represent the number of forward citations for the patent  $p$  of company  $i$  in the technology class  $k$ , while  $N_{ft,k}$  is the total number of forward citations for any patent published in year  $t$  in the same class  $k$ .

To capture the effect of platform technologies, we use the generality index first proposed by Trajtenberg et al. (1997). This is an inversed Herfindahl index calculated using forward patent citations and provides a measure of the spread across different technological fields of follow-up innovations, with values closer to 1 for patents with citations from a large spread across different technological classes and values close to 0 for patents cited in a small number of technological classes. Including the same correction introduced for the dependent variable TECHDIV, the generality index<sup>8</sup> is defined for each patent  $p$  as follows:

$$\text{GENERALITY}_p = \frac{N_{fp}}{N_{fp} - 1} \left( 1 - \sum_{k=1}^K \left( \frac{N_{fp,k}}{N_{fp}} \right)^2 \right) \quad (3a)$$

where  $K$  is the number of different IPC technological classes where patent  $p$  was cited,  $N_{fp,k}$  is the number of forward citations for the  $k$  class and  $N_{fp}$  is the total number of forward citations. Hence, the variable representing the *generality of innovation* (GENIN) is defined as the average of the GENERALITY index for each company  $i$  in year  $t$  as follows:

$$\text{GENIN}_{it} = \frac{1}{P_{it}} \sum_{p_{it}=1}^{P_{it}} \text{GENERALITY}_{p_{it}} \quad (3b)$$

We control for firms' competencies and capabilities with three additional variables. *Knowledge stock* (KSTOCK) represents the accumulated stock of knowledge capabilities for the firms in the data set, measured as the stock of patents accumulated by the company in previous periods of time. Knowledge stock can be seen as a proxy for firms' market value and accumulated innovation capabilities (Hall et al. 2005), compensating for the fact that small firms are not required to report their R&D expenditure. This variable is calculated using the declining balance formula usually proposed in the literature, with the depreciation rate set at 15 % (Hall et al. 2005). KSTOCK enters the estimating equation after being log-transformed. We also add a control variable for the concentration of innovative activity (CONCENTR), which reflects the barriers to innovative entry and the incentives for small firms to explore less 'crowded' technological fields (Almeida and Kogut 1997). The index is calculated as the share of patents held by the largest four innovators in the core technological class of each SSI (Breschi et al. 2003). This variable is also log-transformed. Additionally, we also control for firm age (AGE) as a proxy for the firm's market experience (Nunes et al. 2013). Finally, IPC class dummies are added to control for the differences in the innovative behaviour of small companies related to diverse patterns of industrial dynamics (Marsili 2002; De Jong and Vermeulen 2006); time dummies are used to capture observed and unobserved effects, like business cycles, external to the firms.

#### 4.3 Model estimation

In our analysis, the dependent variable  $y$  is represented by a measure of technological diversification whose values fall within the open bounded interval  $I = (0, 1)$ . Such data do not follow a normal distribution.

<sup>7</sup> Forward citations are all citations made to a specific patent and are commonly used as a proxy for measuring the quality of innovations (Trajtenberg 1990).

<sup>8</sup> By construction, the index is not defined for companies with less than two forward citations per year.

**Table 1** SSIs by IPC class and degree of technological diversification (TECHDIV)

	IPC class	N	% Firms	Patents	% Patents	TECHDIV
1	Electrical engineering	15	4.42	261	3.76	0.49
2	Audiovisual technology	5	1.47	253	3.64	0.45
3	Telecommunications	18	5.31	398	5.73	0.35
4	Information technology	12	3.54	179	2.58	0.49
5	Semiconductors	3	0.88	220	3.17	0.64
6	Optics	11	3.24	195	2.81	0.56
7	Technologies for Control/analysis	28	8.26	534	7.69	0.5
8	Medical engineering	33	9.73	633	9.11	0.3
10	Organic chemistry	8	2.36	169	2.43	0.53
11	Macromolecular chemistry	3	0.88	97	1.40	0.67
12	Pharmaceuticals; cosmetics	34	10.03	759	10.92	0.51
13	Biotechnologies	28	8.26	676	9.73	0.45
14	Agricultural and food products	1	0.29	25	0.36	0
15	Basic chemistry	2	0.59	22	0.32	0.45
17	Materials; metallurgy	3	0.88	40	0.58	0.69
18	Mechanical engineering	11	3.24	251	3.61	0.65
19	Materials processing	4	1.18	57	0.82	0.56
20	Handling; printing	20	5.90	332	4.78	0.45
21	Agricultural and food apparatuses	8	2.36	128	1.84	0.5
22	Environmental technologies	2	0.59	56	0.81	0.45
23	Machine tools	4	1.18	67	0.96	0.33
24	Engines; pumps; turbines	7	2.06	128	1.84	0.43
25	Thermal processes	4	1.18	64	0.92	0.26
26	Mechanical elements	9	2.65	176	2.53	0.69
27	Transport technology	8	2.36	118	1.70	0.39
28	Space technology; weapons	2	0.59	27	0.39	0.06
29	Consumer goods	19	5.60	319	4.59	0.54
30	Civil engineering	37	10.91	764	11.00	0.31
	Total	339	100	6948	100	

Moreover, its bounded nature (between 0 and 1) may lead to predicted values from a standard OLS regression that could lie outside the unit interval. As Papke and Wooldridge point out (1996), the alternative to model the log odds ratio as a linear function is also inappropriate as it cannot handle those cases where the dependent variable equals the interval boundaries zero and one. Adjusting extreme values when these account for a large percentage in the data is also difficult to justify. To account for these issues, we use the fractional response model suggested by Papke and Wooldridge (1996), applying quasi-maximum likelihood estimation (QMLE) to obtain robust estimators of the conditional mean parameters (Papke and Wooldridge 1996; Wooldridge 2010).

The model starts from the assumption that the conditional expectation of the fractional response variable is defined as follows:

$$E(y_i|x_i) = G(x_i\beta) \quad (4)$$

where  $i = 1, \dots, N$  and  $G(\cdot)$  is a cumulative distribution function such as the logistic function  $G(z) = \exp(z)/(1 + \exp(z))$ , which confines  $z$  to the open bounded interval  $I = (0, 1)$ . Following Papke and Wooldridge (1996), it is, then, possible to maximise the Bernoulli log-likelihood function, expressed as follows:

$$l_i(\beta) = y_i \log[G(x_i\beta)] + (1 - y_i) \log[1 - G(x_i\beta)] \quad (5)$$



**Table 2** Descriptive statistics

	Description	Mean	SD	Median	Max	Min	VIF
TECHDIV	Index of technological diversification—dispersion of SSIs' patents across IPC classes	0.45	0.42	0.50	1	0	
RELATEDNESS	Index of relatedness—similarity across new patents and core technological class of SSIs	0.78	0.23	0.83	1	0.21	
TECHDIV_B	Dichotomous variation for the TECHDIV index used in the logit regression	0.53	0.50	1	1	0	
RELATEDNESS_B	Dichotomous variation for the RELATEDNESS index used in the logit regression	0.43	0.49	0	1	0	
OPPOR	Opportunity conditions—rate of change in sectoral patent activity	2.39	1.59	2.18	7.62	−0.82	1.08
IMPIN	Index of innovation impact—ratio of forward citations of SSIs' patents over total forward citations in IPC class	1.14	1.74	0.57	16.96	0	1.03
GENIN	Index of generality—dispersion across IPC classes of forward citations	0.39	0.34	0.39	1	0	1.13
KSTOCK	Firms' knowledge stock—patents accumulated by the company in previous periods of time	10.75	10.23	7.92	104.5	2	1.04
CONCENTR	Concentration index—share of patents in a given technological class held by the largest four innovators	0.03	0.03	0.02	0.32	0	1.16
AGE	Firm age—years since incorporation date	15.85	16.10	10	103	1	1.07

VIF represents the variance inflation factor. Values below 5 indicate the absence of multicollinearity

**Table 3** Fractional response model and logit estimates of technological diversification

Dependent variable	TECHDIV					
	Fractional logit				Logit	
Independent and control variables	(1)		(2)		(3)	
	Odds ratios	SE	Odds ratios	SE	Odds ratios	SE
OPPOR	1.473***	0.206	1.593**	0.305	1.773**	0.691
OPPOR × OPPOR	0.905***	0.018	0.897***	0.024	0.875***	0.034
IMPIN			0.924**	0.033	0.899**	0.040
GENIN			3.479***	0.751	4.915***	1.515
KSTOCK	1.079	0.080	1.009	0.010	1.060	0.145
CONCENTR	1.103***	0.041	1.149***	0.058	1.128	0.087
AGE	1.003	0.004	0.998	0.006	0.989	0.008
Constant	0.491	0.220	0.543	0.307	0.723	0.546
Time dummies	Yes		Yes		Yes	
IPC class dummies	Yes		Yes		Yes	
No. of firms	339		275		275	
No. of observations	1402		757		757	
Pseudo-log likelihood	−801.28		−402.48		−432.45	
AIC	1.211		1.19		1.269	

\*  $p < 0.10$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ —cluster robust SE reported

**Table 4** Fractional response model and logit estimates of technological relatedness

Dependent variable	RELATEDNESS					
Model	Fractional logit				Logit	
Independent and control variables	(1)		(2)		(3)	
	Odds ratios	SE	Odds ratios	SE	Odds ratios	SE
OPPOR	0.674***	0.075	0.658***	0.097	0.578**	0.158
OPPOR $\times$ OPPOR	1.106***	0.019	1.109***	0.026	1.135***	0.046
IMPIN			1.035	0.027	1.114**	0.053
GENIN			0.473***	0.076	0.215***	0.069
KSTOCK	0.868**	0.049	0.893	0.067	0.744**	0.111
CONCENTR	0.926***	0.021	0.902***	0.030	0.781***	0.064
AGE	0.999	0.003	1.002	0.005	1.011	0.009
Constant	6.289***	2.007	5.746***	2.342	3.286	2.551
Time dummies	Yes		Yes		Yes	
IPC class dummies	Yes		Yes		Yes	
No. of firms	339		275		275	
No. of observations	1402		757		757	
Pseudo-log likelihood	−543.79		−293.57		−400.75	
AIC	0.884		0.905		1.183	

\*  $p < 0.10$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ —cluster robust SE reported

to obtain the quasi-maximum likelihood estimator of  $\beta$ , which is consistent regardless of the distribution of  $y_i$  conditional on  $x_i$ , using ordinary logit or probit regression. In line with this approach, we estimate a generalised linear model (GLM) specifying a binomial distribution family, of which Bernoulli is a special case, and using a logit link function (Papke and Wooldridge 1996). Considering the unbalanced structure of the data set with a limited number of observations per panel, we pool our data relying on cluster robust standard errors to account for potential heterogeneity and serial dependence over time (Wooldridge 2010).

As a further check, we also analyse our model using standard maximum likelihood logistic estimation in columns 3 of Tables 3 and 4.<sup>9</sup> In order to run this specification, we are required to convert our dependent variables into binary variables. Accordingly, we define TECHDIV\_B and RELATEDNESS\_B as derivatives of the variables TECHDIV and RELATEDNESS where TECHDIV\_B equals to 1 for all observations

where TECHDIV is  $>0$  and RELATEDNESS\_B equals to a value of 1 when RELATEDNESS is equal to 1.

## 5 Empirical results

The data on technological diversification of SSIs are reported in Table 1. SSIs in a technological class related to mechanical elements and mechanical engineering diversify more, while those firms operating in technology classes traditionally closer to basic science research, such as biotechnology, semiconductors or organic chemistry, seem to be slightly more focused. The least diversified companies are those operating in scale-intensive technology classes such as machine tools, civil engineering and telecommunications.

In Table 2, we report the descriptive statistics for the main variables in our model. Looking at the mean of the index TECHDIV, we see that these companies are clearly diversified in terms of technological activity, but there is a considerable difference across firms with a significant standard deviation reflecting inter-sectoral variations, as shown in Table 1. Over the long period, observable through the index

<sup>9</sup> As in the fractional response model, logit regression is performed using cluster robust standard errors.

RELATEDNESS, SSIs seem to be active in a coherent and more related set of technological classes.

In Tables 3 and 4, we report the estimates from the fractional response model (columns 1 and 2) as well as the logistic model (column 3) for TECHDIV and RELATEDNESS as dependent variables. In both tables, estimates are reported as exponentiated coefficients in order to facilitate the interpretation of the findings. Thus, the estimates reported represent the percentage increase (decrease) in the odds<sup>10</sup> for a one unit increase in the independent variable. In other words, a positive effect is associated with odds ratios being more than 1, while negative effects are present when odds ratios are less than 1.

To study the relationship between technological opportunities and diversification (Table 3), as outlined in our first hypothesis, we start our analysis adding only the linear and quadratic term for OPPOR to account for nonlinearity in the relationship between technological diversification and technological opportunities, along with all control variables. In this specification, both linear and quadratic terms present estimates that are statistically significant at the 0.01 level with a positive and a negative effect, as indicated by the odd ratio being, respectively, more and less than 1. The findings seem to confirm the presence of an inverted-U relationship between technological opportunities and technological diversification. These results are robust to model specifications including also the addition of the explanatory variables IMPIN and GENIN, where the sample size is reduced due to the construction of the index GENIN. In line with previous research on technological diversification, it is possible to argue that SSIs operating in increasingly dynamic industries also expand their technological domain in response to new and promising avenues of research within the technological environment. However, the negative sign for the quadratic term of OPPOR indicates that SSIs might rely on strategies of specialisation once the technological environment becomes highly volatile and turbulent. This inverted-U-shaped relationship seems to suggest that the risk and the resources involved in innovation play a significant role in shaping technological diversification among SSIs. Our findings suggest that the required novelty and the complexity of the innovations developed in

environments characterised by higher technological opportunities and a faster pace of technological advance require the development of specific—and resource intensive—technological competencies that may prevent small companies from diversifying.

In this sense, it is possible to find a resemblance with the ideas of exploration and exploitation (March 1991). As Katila and Ahuja (2002) point out, exploration is important when companies need to find new avenues of research and it is central in the search for completely new solutions. Yet, exploitation can also lead to new knowledge creation, through the recombination of acquired competencies. This process might be particularly important for SSIs operating with rapidly changing technologies, where time and resources for exploration are limited while specific competencies are increasingly valuable.

Considering our second hypotheses on the negative effect of the technological impact of firms' innovations on the degree of technological diversification, we observe that the estimates for the variable IMPIN are negative and statistically significant across model specifications in columns 2 and 3 of Table 3. Small firms that tend to look for new ideas and inspiration in technological fields which are akin to their technological trajectory are more likely to develop specialised competencies (Corradini et al. 2015). Accordingly, it is possible that SSIs with a promising and valuable technology may decide to focus their resources in the same technology area in order to maximise complementarities across their internal competencies. In this sense, another plausible explanation for this finding is that companies working on impactful patents may need to dedicate a larger amount of resources to their further development, in terms of both time and research capabilities. This, in turn, provides further incentives to follow strategies of specialisation.

Looking at the effect of generality, we find evidence of a positive and significant effect on the degree of technological diversification as indicated by the estimated coefficients of the GENIN variable. In line with the third hypothesis, our results indicate that innovations that present broad applicability are likely to provide incentives and opportunities to explore new lines of research in order to exploit the complementarities offered by their development. In other words, technologies with a broad applicability exert a platform effect fostering the diversification of firms'

<sup>10</sup> Odds are defined as the ratio of the probability of success over the probability of failure.

technological trajectory in derivative technologies. Considering the control variables, we find a positive effect of *CONCENTR* on *TECHDIV* which may reflect the need to diversify for SSIs when their core technology class is highly concentrated. Under such circumstances, SSIs may have more incentives to explore areas outside the scope of larger companies that dominate their field, perhaps developing complementary technologies for these very companies. We find that firm age introduces no significant effect on either *TECHDIV* or *RELATEDNESS*. This likely reflects the heterogeneity across innovative SMEs (Ortega-Argilés et al. 2009), with some long established companies being specialised innovators, while newer companies may already be working on a broader set of technologies. These results are robust across all different model specifications, including the logit model in the last column of Table 3.

Similarly, we find evidence supporting our hypotheses when we use *RELATEDNESS* as dependent variable in the model (Table 4). As the dependent variable measures relatedness across SSI' patents, the sign of the coefficients tend to mirror what we found for *TECHDIV*. However, it is important to underline that *RELATEDNESS* directly takes into account the technological distance across IPC fields and the core technological class of SSIs, offering a more nuanced perspective. Looking at *OPPOR*, we find a U relationship with respect to the dependent variable indicating that increasing innovation opportunities lead SSI to innovate in fields progressively distant from their core technological class, but this process reverses in the presence of a turbulent technological environment. Similarly, estimates for *GENIN* reinforce previous findings, indicating the development of enabling technologies may lead SSIs to engage in a more diverse set of innovative activities even when controlling for distance across technological classes.

With respect to the models based on *TECHDIV*, we find two main differences. The first is related to *IMPIN*, which is no longer statistically significant in the fractional response model, reflecting high-impact technologies may not necessarily bring SSIs to focus on patents that are close to their core competencies. Yet, this appears to be the case when looking at the less sensible measure in the logit model. Additionally, when modelling *RELATEDNESS*, we find a negative effect of *KSTOCK* in columns (1) and (3), offering partial evidence that as SSIs increase their

accumulated resources and innovation competencies they are also more likely to engage in processes of exploration across different technological sectors.

## 6 Conclusions

This paper offers novel empirical insights on the patterns and determinants of technological diversification among small serial innovators (SSIs). In particular, the study has explored the role that technology dynamics internal and external to the firm play in shaping the technological trajectory and innovative behaviour of such persistently innovating SMEs by analysing the effect that technological opportunities, as well as the impact and generality of innovation efforts, exert on their degree of technological diversification.

Using patent data from the PATSTAT database for UK-based small serial innovators characterised by a sustained record of innovation activities over time, we show that technological diversification is an existing phenomenon among innovative SMEs. For such companies, technological diversification is argued to result as a consequence of the dynamics of the technology environment within which they operate and the nature and characteristics of the core technology they develop. We find that increasing technological opportunities present an inverted-U relationship with technological diversification. The need to explore growing opportunities pushes SSIs to develop capabilities in an increasing range of technological domains. However, processes of exploration are increasingly balanced out by the need to recombine previous specialised knowledge in the most dynamic and turbulent technological sectors. Firm-specific technology characteristics also matter. High-impact innovations generate incentives to further operate along the same technological trajectory, supporting specialisation patterns built upon cumulated knowledge competencies, whereas enabling technologies open novel opportunities in different technological trajectories, acting as platforms for complementary and derivative technologies. Our results offer further evidence on the significant role that technological dynamics internal and external to the firm have in shaping the innovative behaviour of very innovative small firms. More broadly, our findings highlight the importance of opportunity recognition, innovation

capabilities and technological search beyond the entrepreneurial stage, calling for more research on persistently innovating SMEs.

The results presented should be interpreted taking into account some limitations of the research. First, patent data offer only a partial view on firms' technological capabilities and their innovation activity. Second, given the limited availability of business data for many SMEs, the paper relies mostly on information from patents to control for different characteristics of the companies analysed. Finally, the analysis presented does not take into account the role of innovation networks and collaborations that represent another way through which small firms may acquire complementary innovation capabilities. Similarly, future research should consider the implications of technological diversification for the economic performance of SMEs in order to contribute to the growing literature investigating the impact of innovation on firm growth and performance (Capasso et al. 2015; Hall et al. 2009; Hözl 2009; Stam and Wennberg 2009). These are the next steps in our research.

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## References

- Almeida, P., & Kogut, B. (1997). The exploration of technological diversity and geographic localization in innovation: Start-up firms in the semiconductor industry. *Small Business Economics*, 9, 21–31.
- Antonelli, C., & Scellato, G. (2015). Firms size and directed technological change. *Small Business Economics*, 44(1), 207–218.
- Archibugi, D., Filippetti, A., & Frenz, M. (2013). Economic crisis and innovation: Is destruction prevailing over accumulation? *Research Policy*, 42, 303–314.
- Arora, A., Fosfuri, A., & Gambardella, A. (2001). *Markets for technology*. Cambridge, MA: MIT Press.
- Arthur, W. B. (1994). *Increasing returns and path dependence in the economy*. Ann Arbor: University of Michigan Press.
- Audretsch, D. (1995). *Innovation and industry evolution*. Cambridge: MIT Press.
- Brancati, E. (2015). Innovation financing and the role of relationship lending for SMEs. *Small Business Economics*, 44(2), 449–473.
- Breschi, S., Lissoni, F., & Malerba, F. (2003). Knowledge-relatedness in firm technological diversification. *Research Policy*, 32, 69–87.
- Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth'? *Journal of Econometrics*, 6, 83–108.
- Brown, S. L., & Eisenhardt, K. M. (1995). Product development: Past research, present findings, and future directions. *Academy of Management Review*, 20(2), 343–378.
- Capasso, M., Treibich, T., & Verspagen, B. (2015). The medium-term effect of R&D on firm growth. *Small Business Economics*, 45(1), 39–62.
- Chiu, Y., Lai, H., Liaw, Y., & Lee, T. (2010). Technological scope: Diversified or specialized. *Scientometrics*, 82, 37–58.
- Coad, A., & Guenther, C. (2013). Diversification patterns and survival as firms mature. *Small Business Economics*, 41, 633–649.
- Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35, 128–152.
- Colombo, M. G., Piva, E., & Rossi-Lamastra, C. (2014). Open innovation and within-industry diversification in small and medium enterprises: The case of open source software firms. *Research Policy*, 43, 891–902.
- Corradini, C., Battisti, G., & Demirel, P. (2015). Serial innovators in the UK: Does size matter? *Industrial and Corporate Change*. doi:10.1093/icc/dtu040.
- Cyert, R. M., & March, J. G. (1963). *A behavioral theory of the firm*. Englewood Cliffs, NJ.
- David, P. A. (1985). Clio and the economics of QWERTY. *The American Economic Review*, 75, 332–337.
- De Jong, J. P. J., & Vermeulen, P. A. M. (2006). Determinants of product innovation in small firms: A comparison across industries. *International Small Business Journal*, 24(6), 587–609.
- Deschryvere, M. (2014). R&D, firm growth and the role of innovation persistence: An analysis of Finnish SMEs and large firms. *Small Business Economics*, 43, 767–785.
- Dosi, G. (1982). Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11, 147–162.
- Dosi, G., & Nelson, R. R. (2013). The evolution of technologies: An assessment of the state-of-the-art. *Eurasian Business Review*, 3, 3–46.
- Fai, F. (2003). *Corporate technological competence and the evolution of technological diversification*. Cheltenham: Edward Elgar Publishing.
- Fai, F., & Von Tunzelmann, N. (2001). Industry-specific competencies and converging technological systems: Evidence from patents. *Structural change and economic dynamics*, 12, 141–170.
- Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science*, 47, 117–132.
- Gambardella, A., & Torrisi, S. (1998). Does technological convergence imply convergence in markets? Evidence from the electronics industry. *Research Policy*, 27(5), 445–463.
- García-Quevedo, J., Pellegrino, G., & Vivarelli, M. (2014). R&D drivers and age: Are young firms different? *Research Policy*, 43, 1544–1556.



- Garcia-Vega, M. (2006). Does technological diversification promote innovation? An empirical analysis for European firms. *Research Policy*, 35, 230–246.
- Granstrand, O. (1998). Towards a theory of the technology-based firm. *Research Policy*, 17, 465–489.
- Granstrand, O., Patel, P., & Pavitt, K. (1997). Multi-technology corporations: Why they have ‘distributed’ rather than ‘distinctive core’ competencies. *California Management Review*, 39, 8–25.
- Hall, B. H. (2005). A note on the bias in herfindahl-type measures based on count data. *Revue d'Economie Industrielle. Programme National Persee*, 110, 149–156.
- Hall, B. H., Jaffe, A., & Trajtenber, M. (2005). Market value and patent citations. *The Rand Journal of Economics*, 36, 16–38.
- Hall, B., Lotti, F., & Mairesse, J. (2009). Innovation and productivity in SMEs: Empirical evidence for Italy. *Small Business Economics*, 33, 13–33.
- Hicks, D., & Hegde, D. (2005). Highly innovative small firms in the markets for technology. *Research Policy*, 34, 703–716.
- Hölzl, W. (2009). Is the R&D behaviour of fast-growing SMEs different? Evidence from CIS III data for 16 countries. *Small Business Economics*, 33, 59–75.
- Katila, R., & Ahuja, G. (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, 45, 1183–1194.
- Kim, D. J., & Kogut, B. (1996). Technological platforms and diversification. *Organization Science*, 7, 283–301.
- Kim, M., & Wang, I. K. (2014). Dynamic product differentiation strategies: An examination of the interplay of firm and industry characteristics. *Technology Analysis & Strategic Management*, 26(8), 959–983.
- Klevorick, A. K., Levin, R. C., Nelson, R. R., & Winter, S. G. (1995). On the sources and significance of interindustry differences in technological opportunities. *Research Policy*, 24, 185–205.
- Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science*, 3, 393–397.
- Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal*, 13, 111–125.
- Leten, B., Belderbos, R., & Van Looy, B. (2007). Technological diversification, coherence, and performance of firms. *Journal of Product Innovation Management*, 24, 567–579.
- Libaers, D., & Meyer, M. (2011). Highly innovative small technology firms, industrial clusters and firm internationalization. *Research Policy*, 40, 1426–1437.
- Lin, C., & Chang, C. C. (2015). The effect of technological diversification on organizational performance: An empirical study of S&P 500 manufacturing firms. *Technological Forecasting and Social Change*, 90, 575–586.
- Malerba, F., Mancusi, M., & Montobbio, F. (2013). Innovation, international R&D spillovers and the sectoral heterogeneity of knowledge flows. *Review of World Economics*, doi:10.1007/s10290-013-0167-0.
- Malerba, F., & Orsenigo, L. (1993). Technological regimes and firm behaviour. *Industrial and Corporate Change*, 2, 45–71.
- Máñez, J. A., Rochina-Barrachina, M. E., Sanchis-Llopis, A., & Sanchis-Llopis, J. A. (2015). The determinants of R&D persistence in SMEs. *Small Business Economics*, 44, 505–528.
- March, J. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2, 71–87.
- Marsili, O. (2002). Technological regimes and sources of entrepreneurship. *Small Business Economics*, 19, 217–231.
- Martinez, C. (2011). Patent families: When do different definitions really matter? *Scientometrics*, 86, 39–63.
- McGrath, R. G., & Nerkar, A. (2004). Real options reasoning and a new look at the R&D investment strategies of pharmaceutical firms. *Strategic Management Journal*, 25(1), 1–21.
- Miller, D. J. (2006). Technological diversity, related diversification, and firm performance. *Strategic Management Journal*, 27, 601–619.
- Modrego, F., McCann, P., Foster, W. E., & Olfert, M. R. (2015). Regional entrepreneurship and innovation in Chile: A knowledge matching approach. *Small Business Economics*, 44(3), 685–703.
- Mowery, D., & Rosenberg, N. (1998). *Paths to innovation*. Cambridge: Cambridge University Press.
- Narula, R. (2004). R&D collaboration by SMEs: New opportunities and limitations in the face of globalisation. *Technovation*, 24, 153–161.
- Nelson, R. R., & Winter, S. (1982). *An evolutionary theory of economic change*. Cambridge, MA: Belknap Press.
- Nesta, L., & Saviotti, P. P. (2005). Coherence of the knowledge base and the firm’s innovative performance: Evidence from the U.S. pharmaceutical industry. *The Journal of Industrial Economics*, 53, 123–142.
- Newey, L. R., & Zahra, S. A. (2009). The evolving firm: How dynamic and operating capabilities interact to enable entrepreneurship. *British Journal of Management*, 20, S81–S100.
- Nunes, P. M., Goncalves, M., & Serrasqueiro, Z. (2013). The influence of age on SMEs’ growth determinants: Empirical evidence. *Small Business Economics*, 40, 249–272.
- OECD. (2001). *Science, technology and industry scoreboard: Towards a knowledge-based economy*. Paris: OECD Publishing.
- Ortega-Argilés, R., Vivarelli, M., & Voigt, P. (2009). R&D in SMEs: A paradox? *Small Business Economics*, 33(1), 3–11.
- Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *Journal of Applied Econometrics*, 11, 619–632.
- Patel, P., & Pavitt, K. (1997). The technological competencies of the world’s largest firms: Complex and path-dependent, but not much variety. *Research Policy*, 26, 141–156.
- Patel, P., & Pavitt, K. (1998). The wide (and increasing) spread of technological competencies. In the world’s largest firms: A challenge to conventional wisdom. In A. D. Chandler, P. Hageström, Ö. Slöfvel (Eds.), *The Dynamic Firm. The Role of Technology, Strategy, Organization, and Regions*. Oxford: Oxford University Press.
- Peters, B. (2009). Persistence of innovation: Stylised facts and panel data evidence. *The Journal of Technology Transfer*, 34, 226–243.

- Quintana-Garcia, C., & Benavides-Velasco, C. (2008). Innovative competence, exploration and exploitation: The influence of technological diversification. *Research Policy*, 37, 492–507.
- Rammer, C., Czarnitzki, D., & Spielkamp, A. (2009). Innovation success of non-R&D-performers: Substituting technology by management in SMEs. *Small Business Economics*, 33, 35–58.
- Raymond, W., Mohnen, P., Palm, F., & Van Der Loeff, S. S. (2010). Persistence of innovation in Dutch manufacturing: Is it spurious? *The Review of Economics and Statistics*, 92, 495–504.
- Rothwell, R., & Dodgson, M. (1994). Innovation and size of firm. In M. Dodgson (Ed.), *Handbook of industrial innovation* (pp. 310–324). Aldershot: Edward Elgar.
- Schmoch, U. (2008). *Concept of a technology classification for country comparisons*. Final report to the World Intellectual Property Organisation (WIPO). [http://www.wipo.int/edocs/mdocs/classifications/en/ipc\\_ce\\_41/ipc\\_ce\\_41\\_5-annex1.pdf](http://www.wipo.int/edocs/mdocs/classifications/en/ipc_ce_41/ipc_ce_41_5-annex1.pdf).
- Stam, E., & Wennberg, K. (2009). The roles of R&D in new firm growth. *Small Business Economics*, 33(1), 77–89.
- Stuart, T., & Podolny, J. (1996). Local search and the evolution of technological capabilities. *Strategic Management Journal*, 17, 21–38.
- Suzuki, J., & Kodama, F. (2004). Technological diversity of persistent innovators in Japan: Two case studies of large Japanese firms. *Research Policy*, 33, 531–549.
- Toh, P. K., & Kim, T. (2013). Why put all your eggs in one basket? A competition-based view of how technological uncertainty affects a firm's technological specialization. *Organization Science*, 24, 1214–1236.
- Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. *The Rand Journal of Economics*, 21, 172–187.
- Trajtenberg, M., Henderson, R., & Jaffe, A. (1997). University versus corporate patents: A window on the basicness of invention. *Economics of Innovation and New Technology*, 5(1), 19–50.
- Tushman, M. L., & Rosenkopf, L. (1992). Organizational determinants of technological-change-toward a sociology of technological evolution. *Research in Organizational Behavior*, 14, 311–347.
- Vossen, R. W. (1998). Relative strengths and weaknesses of small firms in innovation. *International Small Business Journal*, 16, 88–95.
- Wang, Q., & von Tunzelmann, N. (2000). Complexity and the functions of the firm: Breadth and depth. *Research Policy*, 29, 805–818.
- Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). Cambridge: MIT Press.